REACT: The Riskmap Evaluation and Coordination Terminal

by

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Abstract

The United Nations Office for Disaster Risk Reduction (UNDRR) states that economic losses due to natural disasters have risen 151 percent in the past 20 years. Of these disasters, floods are the most common. The Sendai Framework for Disaster Risk Reduction was created by the UNDRR in order to chart goals for future risk mitigation; among its seven global targets is increasing the availability of disaster risk information and assessment systems. Disaster information systems use state of the art techniques such as remote sensing in order to mitigate damages from natural and man made hazards.

More developed countries utilize networks of advanced sensors and ahead of time mapping in order to facilitate emergency responses; however, such systems are not available in developing countries due to cost limitations. The widespread proliferation of smart phones and social media use in developing countries means that citizens can be used as sensors by reporting disaster information online. The Riskmap system was developed by the Urban Risk Lab at MIT in order to gather citizen report streams. Such citizen disaster reports have two issues: a large influx of reports can cause information overload in emergency operations centers, which makes it difficult to summarize the situation. Machine learning has previously been used in order to analyze and simplify information for human consumption. This work seeks to use novel machine learning techniques to fully utilize crowdsourced social media reports gathered using the Riskmap system.

First we establish the motivation for using citizens as sensors and analyzing this noisy data using machine learning. We then review different machine learning techniques that have been used in crisis information systems, including those that also utilize social media. Finally a novel ensemble learning model is presented that can accurately predict large flood events from crowdsourced data.

Thesis Supervisor: Miho Mazereeuw
Title: Associate Professor

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Chapter 1

Introduction

Flooding is the most common natural disaster in the world [5]. Flood related deaths account for half of all deaths from natural disasters [14]. Although flooding impacts both developed and developing countries, developing nations face much worse consequences as a result of flooding since they lack resources to adequately mitigate disasters [17]. Unregulated urbanization, rising population and climate change are all contributing to increase the rate at which floods occur in developing megacities; furthermore, there is little data about these disasters [10]. Data scarcity makes it hard to pinpoint where to direct aid during disasters and where to make infrastructure improvements after disasters [18].

Various stakeholders have different but overlapping interests with regards to disaster management. Government and NGOs work together to provide relief from mitigate damages from flooding [4]. Citizens look for relevant flood information and try to reduce their risk [27]. Information is at the core of this interaction; however, data scarcity makes it hard for emergency personnel to optimize their use of resources, while citizens have an abundance of information about their surroundings but must be careful not to trust incorrect or outdated information about broader areas [16]. The natural solution is for citizens on social media to submit real time reports to the Emergency Operations Center (EOC), which is tasked with using those reports to inform citizens. There is one problem with this solution, in times of crisis EOCs can suffer from information overload when they are presented with too much information [22].

The REACT system uses novel machine learning and human computer interaction research to reduce information overload in EOCs, thereby decreasing disaster response time. REACT learns how Emergency Operations Centers (EOCs) classify the severity of flood events given citizen submitted reports. REACT trains itself through a gamified simulation of a disaster event. During a real disaster, REACT digests social media reports and estimates how severely an event is impacting different areas of a city and thereby helps EOCs to respond in the best manner possible.

1.1 Emerging Risk In South and Southeast Asia

Global climate change is 'expected to increase the frequency and intensity of floods' [1]. Urban areas are particularly at risk from flooding; unchecked development and rising population have created megacities that regularly experience flooding [5]. Nowhere is this more apparent than in South and Southeast Asia, where the severity of floods has been increasing over the past several decades [23].

Of the world's 33 megacities, over 60 percent are located in developing Asian Countries [25]. These cities face a looming crisis as flood risk increases, but there are also unique opportunities for risk mitigation. Megacities are characterized by high population density. This high density leads to an increase in economic damages and loss of life, but it also means that there are large numbers of citizens that have disaster information they'd like to share with others [5].

1.2 History of Disaster Informatics

Work in Mapping disasters Epidemiology John Snow's use of maps to find the source of Cholera outbreak in London[19].

In more recent times, the need for Information Technology (IT) in disaster management has been clear since the mid 1980s when computers became user friendly enough to be used during disasters [26]. Now many EOCs use Geographic Information Systems (GIS) in order to organize spatial data and analyze disaster information; however, researchers have often stated that ‘there are many reasons to remain skeptical about the idea that technology will provide a panacea for emergency management problems’ [24, 22, 15]. A number of potential negative effects associated with IT disaster management technology have been identified: the potential for the technology to increase social inequality, the potential of information overload, and the dissemination of incorrect and outdated information (Quarantelli 1997; Flentge et al., n.d.).

For flooding: [1]

Technology can help disaster response; however, it also has the ability to cause information overload[22]

1.2.1 Social Media and disasters

The history of social media and the hashtag is invariably linked to disaster communication. It was during the San Diego bush fires of 2007 that hashtags were first widely used on twitter [20].

Much work has been done in passively listening to social media streams in order to better understand how disasters unfold and how humans use social media as a communication tool during disaster events. Many of these studies use hand labeled tweets in order to analyze which percentage of them

Digital Humanitarians use twitter to help spatially locate needs in Haiti after the 2008 earthquake [10]

Twitter tale of 3 hurricanes [2]

1.2.2 Machine Learning and Social Media

1.3 The Riskmap System

1.3.1 Motivation for crowdsourced data

Citizens as sensors Geosocial intelligence Holderness [8] 1.3.

Quarantelli emphaszied that ‘management of hazards is fundamentally social in nature and not something that can be achieved strictly through technological upgrading’ [22] yet social media brings human behavior into a machine readable format that can be used to provide further information during disasters.

1.3.2

Chapter 2

Previous Work

2.1 Machine Learning in Crisis Informatics

2.1.1 Passive Listening

Most of the work in this area has been done by passively listening to twitter posts or facebook comments.

Some was looking for clues after disasters: [27] problem: don't have real time results

Some used humans to filter out social media for real time disaster info [21] [10]

Some involved using machine learning: [9]

Problems with that approach:

It is very difficult to filter out which social media images are related to the disaster and which are not.

2.1.2 On Image Data

Online learning using traditional transfer learning [7] but online (so they get people to label images as a disaster happens?) plus train with generic disaster images in order to solve cold start problem at the beginning of an event. Classify social media images into 3 classes: (severe, mild, little) damage. [12]

2.1.3 On Text Data

Crowd sentiment detection during disasters using twitter and the 2010 San Bruno CA fires n=3698 [11]

Feature engineering on twitter messages to classify into pre-incident, during incident and post-incident [6]

Classifying tweets as informative/ not informative using CNNs vs SVMs (CNN wins) [3]

CrisisNLP from the Qatar Computing Research Institute has a huge datasets [13]

2.1.4 Ensemble Data Models

2.1.5 Common Difficulties

Task Subjectivity

Task subjectivity is an incredibly common issue [12, 17]. While most humans can agree on whether an object is or is not an apple, this task does not translate to defining if a picture indicates a severe event or a minor one.

In other words, people's perception of risk varies widely from region to region and from citizen to citizen [17].

Small datasets

For example [11] only uses 3,698 tweets.

Chapter 3

Methodology

3.1 Data Description

The Riskmap system allows citizens to easily submit disaster reports 1.3; as such it has allowed the Urban Risk Lab at MIT to gather thousands of reports of real flooding in Indonesia and India.

3.1.1 Image Data

3.1.2 Text Data

3.1.3 Flood Height

3.1.4 Location Information

Chapter 4

Results

4.1 Individual

4.1.1 Image Data

4.1.2 Text Data

4.1.3 Flood Height

4.1.4 Location Information

4.2 Bagging

Appendix A

Tables

Table A.1: Armadillos

Armadillos	are
our	friends

Appendix B

Figures

Figure B-1: Armadillo slaying lawyer.

Figure B-2: Armadillo eradicating national debt.

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